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Determinants of Full Child Immunization; Evidence from Ethiopia

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Abstract: *Background:* Immunization is one of the main health interventions to prevent childhood morbidity and mortality. The health of under 5 children has been a major problem in developing countries like Ethiopia. Immunization will become more effective if the child receive the full course of recommended immunization doses. *Objective:* The main objective of this study is to statistically identify and analyze the various possible determinants of full immunization among children in rural and urban households of SNNPRS, Ethiopia. *Design:* The sampling technique employed was multistage stratified cluster sampling. *Results:* Analysis of the study revealed that only 18.3% of children under 5 years of age are fully immunized in the region. Results of the multiple binary logistic regression show that place of residence, age of the child, educational status of mothers, access to media and place of child delivery are the most important determinant factors affecting full child immunization (p-value<5%) in the region. It is observed that children living in rural parts of the region whose community is usually facing shortage of basic services like education, access to media and health services are at higher risk of complete immunization. *Conclusion:* Primary health care and education programs which would fit the features of the region should be designed and implemented to safeguard children from immunization deficiency.

Keywords: Full Childhood Immunization, SNNPPR, Ethiopia, EDHS

1. Introduction

Immunization is a means of protecting a human being against specific diseases by building up the body defense system. This is done by giving vaccines either through injection or by mouth. Performance of immunization programs is more commonly measured by coverage, ensuring that every child is immunized at the earliest/ appropriate age, which is an important public health goal. Immunization coverage is one of the indicators used to monitor progress towards the achievement of MDG4 (reducing child mortality by 3/4), as it is one of the most cost-effective public health interventions for reaching the millennium goals (UN, 2008).

Since 1960s, prevention methods such as childhood vaccinations are the main reason for improvement in child survival in developing world. The global Universal Childhood Immunization initiative goals for Routine Immunization (RI) are 80% coverage (Callreus, 2010).The Expanded Program on Immunization (EPI) of the WHO consists vaccination against six childhood diseases: polio, measles, pertussis, tetanus, diphtheria, and tuberculosis. Although the campaign to immunize the children against life threatening diseases was started in 1979, Ethiopia seriously considered the EPI effort when it made its commitment at the United Nations to reach child immunization by 1990. The achievement of immunization in Ethiopia has been impressive (CSA, 2011).

According to the guidelines developed by the WHO, children are considered as fully vaccinated when they have received a vaccination against tuberculosis (BCG), three doses each of the DPT and polio vaccines, and a measles vaccination by the age of 12 months. The pentavalent vaccine DPT-HepB-Hib, introduced in 2007, has replaced the previous DPT vaccine. This new vaccine protects against diphtheria, pertussis (whooping cough), tetanus, hepatitis B, and Haemophilus influenza type b (WHO, 2008).

According to 2011 EDHS, only 24 percent of children were fully vaccinated at the time of the survey in a countrywide. While this represents a 19 percent increase from the level reported in the 2005 EDHS, the number of children who are fully vaccinated remains far below the goal of 66 percent coverage set in the HSDP IV (CSA, 2011).

Vaccine preventable diseases account for 25% of all deaths occurring annually among children Under- Five (WHO, 2008). UNICEF in 2003 estimated that almost 3 million children's lives were saved each year from immunization. Currently, around 2 million children are still dying every year from Vaccine-preventable diseases (UNICEF, 2012).

More than 10 million of the child deaths each year are caused by lack of application of evidence based, cost effective prevention methods (Black, et al., 2010). Reducing child mortality has positive sequlea such as reduced fertility, which can lead to empowerment of women and can affect performance in the other MDGs. Reducing child morbidity ensures that there is a healthy and robust generation contributing to the society.

An understanding of the factors associated with the acceptance of immunization services have considerable importance for planners and policy-makers to bridge the gap between the immunization potential and actual performance of the program. Additionally information on immunization coverage is important for monitoring and evaluation of programs on immunization. Thus an investigation of the factors associated with the acceptance of immunization services has critical importance.

The main objective of this study is to statistically identify and analyze the various possible determinants of full immunization among children in rural and urban households of SNNPRS, Ethiopia. The Specific Objectives are:

1) To describe the coverage of childhood immunization status among children in the region.
2) To assess the overall situation of children in the study area.
3) To describe the extent of the variation in child immunization between rural and urban parts of the region.
4) To provide information for policy makers and researchers.

2. Methods

Southern Nations, Nationalities, and People's Regional State (often abbreviated as SNNPRS) is one of the nine ethnic divisions (kililoch) of Ethiopia. It was formed from the merger of the former Regions 7-11 following the 1994 elections. Its capital is Hawassa.

The Southern Nation, Nationalities and Peoples Regional State (SNNPRS) is the most multi–ethnic regional state of Ethiopia. It is the region representing people from varieties of large nations and numerous small nationalities with distinct language, tradition, culture and custom. SNNPRS is also unique in that it represents an extensive geographic area and a large population of high diversity that live in unity.

SNNPRS borders Kenya to the south, Kenya and South Sudan to the southwest, South Sudan to the west, Gambela to the northwest, and Oromia to the north and east. The livelihood of the region's population is primarily dependent on sedentary agriculture while a large proportion is also dependent on livestock production, especially in the pastoral and agro-pastoral areas bordering with Kenya. Even though SNNPRS is one of the most fertile regions, it is one of the regions where the coverage of basic public services like education, health, clean water supplyetcare still not satisfactory.

This research utilizes the Ethiopian 2011 Demographic and Health Survey (EDHS, 2011) as its source of data which is the third comprehensive and nationally representative population and health survey. The data type is cross-sectional, that is, the data is collected from sampling units at the same time and the study type is exploratory.

The 2007 Population and Housing Census, conducted by the CSA, provided the sampling frame to draw this sample. Administratively, regions in Ethiopia are divided into zones, and zones, into administrative units called weredas. Each wereda is further subdivided into the lowest administrative unit, called kebele. The 2011 EDHS sample was selected using a stratified, two-stage cluster design. A complete listing of households was carried out in each of the 624 selected enumeration areas. Thus data regarding to this study is collected on a total of around981 children under the age of 59 months in the households of selected clusters.

2.1. Study Variables

2.1.1. The Response Variable

The dependent or response variable of this study is immunization status of a child, which is grouped into two Categories; those who are fully immunized and those who are not fully immunized. In this paper a child is considered as fully immunized if he or she has received all of the vaccinations-BCG, three doses of DPT and Polio (which usually starts from the one and half months of child's age), and Measles (which starts from 9 months of age) at the time of survey (Based on the guideline developed by WHO, 2008).

2.1.2. Explanatory Variables

In this study factors that affect children to get access of vaccination services are classified in to socio-economic, demographic and community factors.

A. Socio-Economic Characteristics

As proxy indicators of socioeconomic characteristics, the following factors are included:-place of residence, mother's educational status, educational status of mothers' partner,, place of child delivery and household wealth index.

B. Demographic Characteristics

Demographic characteristics included are: age of the child, sex of the child, number of under 5 children in the family and desire for more children.

C. Community Characteristics

There are certain community characteristics that may increase or decrease the likelihood to get accesses of vaccination services among children in the region; such as, exposure to mass media, availability of electric power and distance from health centers.

2.2. Binary Logistic Regression Model

Logistic regression analysis extends the techniques of multiple regression analysis in which the outcome variable is categorical (nominal or ordinal scale). Logistic regression allows one to predict a discrete outcome, such as group membership, from a set of predictor variables that may be continuous, discrete, dichotomous, or a mix of any of these (Gellman and Hill, 2007).

Generally, when the dependent variable is dichotomous (such as presence or absence, success or failure and etc) binary logistic regression is used. Unlike discriminant analysis, logistic regression does not requires the independent variables to be normally distributed, linearly related and equal variance with in each group (Tabachnick and Fidel, 1996). The main uses of logistic regression are predicting the group membership, since logistic regression calculates the probability of success over the probability of failure and provides knowledge of the relationships and strengths among the variables.

The response variable of this study is childhood immunization status is dichotomous and denoted by $Y_i, i = 1,2,\dots,n$ which is a Bernoulli random variable with two possible values, $y_i = 1$, with probability of not fully vaccinated $P_i = P(y_i = 1|X_i)$ and $y_i = 0$, with probability of fully vaccinated, $1 - P_i = 1 - P(y_i = 1|X_i)$.

The logistic regression model is defined as follows: Let $Y_{n\times 1}$ be a dichotomous outcome random variable with categories 1 (not fully vaccinated) and 0 (fully vaccinated) and let $X_{(n\times(k+1))}$ denote the collection of k-predicator variables.

$$\text{Where, } \mathbf{X} = \underbrace{\begin{pmatrix} 1 & X_{11} & X_{12} & \dots & X_{1k} \\ 1 & X_{21} & X_{22} & \dots & X_{2k} \\ . & . & . & \dots & . \\ . & . & . & \dots & . \\ . & . & . & \dots & . \\ 1 & X_{n1} & X_{n2} & \dots & X_{nk} \end{pmatrix}}_{n\times(k+1)} = \begin{bmatrix} X_1 \\ X_2 \\ . \\ . \\ . \\ X_n \end{bmatrix}$$

X is called regression matrix, and without the loading column of 1's, is termed as predictor data matrix. Then, the conditional probability that the i^{th} child is not fully vaccinated given the vector of predictor variables, X_i is denoted by $P_i = P(y_i = 1|X_i)$. The expression P_i in logistic regression model can be expressed in the form of:

$$P_i = P(y_i = 1|X_i) = \frac{e^{X_i\beta}}{1 + e^{X_i\beta}}, i = 1,2,\dots,n$$

Where $P(y_i = 1|X_i)$ is the probability of ith child is not fully immunized given the child's individual characteristics x_i , and $\beta = (\beta_0, \beta_1, \dots, \beta_k)^T$ is a vector of unknown coefficients with dimension of $(k + 1) \times 1$.

However, the relationship between the probability of ith child has not received all vaccination services and his/her characteristics is non linear. In order to make meaningful interpretation, the probability of ith child is not fully vaccinated can be written as linear combinations of predictors. This is computed using the logit transformation which is given by:

$$logit[P_i] = log\left(\frac{P_i}{1 - P_i}\right) = \sum_{j=0}^{k} \beta_j X_{ij}, i = 1,2,\dots n; j = 0,1,\dots,k,$$

Where, $X_{i0} = (1,1,\dots,1)^T$

The coefficient of a continuous covariate is interpreted as the change in the log-odds of being not fully vaccinated per unit increment in corresponding covariate. In case of categorical predictor variable, it is interpreted as the log-odds of being not fully vaccinated among children with a given category compared to the reference category.

2.3. Parameter Estimation in Logistic Regression Model

The maximum likelihood and non-iterative weighted least squares are the two most computing estimation methods used in fitting logistic regression model (Hosmer and Lemeshow, 1989). When the assumption of normality of the predictors does not hold, the non- iterative weighted least squares method is less efficient (Maddala, 1997). In contrast, the maximum likelihood estimation method is appropriate for estimating the logistic model parameters due to this less restrictive nature of the underlying assumptions (Hosmer and Lemeshow, 1989). Hence, in this study the maximum likelihood estimation technique is used to estimate parameters of the model.

Consider the logistic model $P(y_i = 1|X_i) = \frac{e^{X_i\beta}}{1+e^{X_i\beta}}$. Since observed values of $Y(Y_i, i = 1,2,\dots,n)$ are independently distributed as Bernoulli random variables, the maximum likelihood function of$y$ is the joint density funcion given by:

$$L(\beta|Y) = \prod_{i=1}^{n} P(y_i = 1|X_{i1},\dots,X_{ik})$$

$$= \prod_{i=1}^{n} \left[\frac{e^{X_i\beta}}{1 + e^{X_i\beta}}\right]^{y_i} \left[\frac{1}{1 + e^{X_i\beta}}\right]^{1-y_i}$$

The maximum likelihood estimates of the parameters β are obtained by maximizing the log-likelihood function which is given by:

$$logL(\beta|Y) = \sum_{i=1}^{n} \left\{ y_i log\left[\frac{e^{X_i\beta}}{1 + e^{X_i\beta}}\right] + (1 - y_i) log\left[\frac{1}{1 + e^{X_i\beta}}\right] \right\}$$

The maximum likelihood estimate of the parameter is found by the derivation of the log-likelihood function with respect to each β's and set each equation to zero which is given as:

$$\frac{dlogL(\beta|Y)}{d\beta_j} = 0, j = 1,2,\dots,k$$

2.4. Odds Ratios

The odds ratio is the ratio of the odds of an event occurring in one group to the odds of occurring in another group**.** The odds ratio (OR) is a popular measure of the strength of association between exposure and the problem. In a cohort study, the odds ratio is expressed as the ratio of the number of cases to the number of non-cases in the exposed and unexposed groups (Cornfield, 1951).

In binary logistic regression, odds ratio is the exponential of the estimated coefficient $\hat{\beta}$ $(exp(\hat{\beta}))$. For continuous covariate; $exp(\hat{\beta})$ is the predicted change in odds of being not fully immunized for a unit increase in predictor variable. In case of categorical predictor variable, $exp(\hat{\beta})$ is the predicted change in odds of being not fully immunized for a given category of the predictor variable with respect to the reference category.

2.5. Assessment of Fitness of the Model

A. Goodness of Fit of the Model

The goodness of fit or calibration of a model measures how well the model describes the response variable. Assessing goodness of fit involves investigating how close values are predicted by the model with that of observed values (Bewick et al., 2005). The comparison of observed to predicted values using the likelihood function is based on the statistic called deviance.

$$D = -2\sum_{i=2}^{n}\left[y_{i.}ln\left(\frac{\hat{\pi}_{i.}}{y_{i.}}\right) + (1-y_{i.})ln\left(\frac{1-\hat{\pi}_{i.}}{1-y_{i.}}\right)\right]$$

For purposes of assessing the significance of an independent variable, the value of Dare compared with and without the independent variable in the equation as given below:

$$D = D_o - D_L$$

Where D_0 -deviance of model without the explanatory variable and D_1 -deviance of model with the explanatory variable included. The goodness-of-fit Devaluates predictors that are eliminated from the full model, or predictors (and their interactions) that are added to a smaller model. In general, as predictors are added or deleted, log-likelihood decreases or increases. The question in comparing models is whether the log-likelihood decreases or increases significantly with the addition or deletion of predictor(s) in the model. D has a chi-square distribution with degree of freedom equal to the difference between the numbers of parameters estimated in the two models.

B. Likelihood-Ratio Test

An alternative and widely used approach to test the significance of a number of explanatory variables is to use the likelihood ratio test. This is appropriate for a variety of types of statistical models. Agresti, 1990; argues that the likelihood ratio test is better, particularly if the sample size is small or the parameters are large. The G^2 test statistic is defined as two times the natural log of the ratio of likelihood functions of two models evaluated at their Maximum Likelihood Estimates (MLEs). The likelihood-ratio test uses the ratio of the maximized value of the likelihood function for the full model (L_1) over the maximized value of the likelihood function for the reduced model (L_0). For each of the variables removed from the full model once a time, MLEs are computed and likelihood function L_0 is calculated. Therefore, the likelihood-ratio test statistic is given by:

$$G^2 = -2\ln\left[\frac{L_0}{L_1}\right] = -2\{\ln L_0 - \ln L_1\}$$

Where L_0 is the likelihood function of the null model andL_1 is the likelihood function of the full model evaluated at the MLEs. This natural log transformation of the likelihood functions yields an asymptotically chi-squared statistic. G^2 is distributed with degree of freedom equal to the difference between the numbers of parameters estimated in the two models (Menard, 2002). It tests the null hypothesis that all population logistic regressions coefficients are zero except the constant one.

C. The Hosmer and Lemeshow Test Statistic

The final measure of model fit is the Hosmer and Lemeshow goodness-of-fit statistic, which measures the correspondence between the actual and predicted values of the dependent variable. Hosmer and Lemeshow chi-square test is used to test the overall model goodness-of-fit test. Hosmer and Lemeshow test is based on grouping cases in deciles in the sense that it is obtained by applying a chi-square test on a 2×g (groups) contingency table. The contingency table is constructed by cross classifying the dichotomous dependent variable with approximately g=10 groups in which the groups are formed by partitioning the predicted probabilities using the percentiles of the predicted event probability. It evaluates the goodness-of-fit by creating these 10 ordered groups of subjects and then compares the number actually in the each observed group to the number predicted by the logistic regression model. The 10 ordered groups are created based on their estimated probability in such that those with estimated probability below 0.1 form one group, and so on, up to those with probability 0.9 to 1. Each of these categories is further divided into two groups based on the actual observed outcome variable (success, failure).The expected frequencies for each of the cells are obtained from the model. If the model is good, most of subject with success are classified in the higher deciles of risk and those with failure in the lower deciles of risk and if the significance of the test is less than 0.05, then the model does not adequately fit the data. Thus, the test statistic is a chi-square statistic with a desirable outcome of non significance, indicating that the model prediction does not significantly differ from the observed. The Hosmer and Lemeshow test statistic is given by:

$$\hat{C} = \sum_{k=1}^{g}\frac{(O_k - E_k)^2}{V_k}$$

Where $E_k = nP_k, V_k = nP_k(1 - P_k)$, g the number of group is, O_k is observed number of events in the k^{th} group, E_k is expected number of events in the k^{th} group, and V_k is a variance correction factor for the k^{th} group. If the observed number of events differs from what is expected by the model, the statistic $\hat{C}$ will be large and there will be evidence against the null hypothesis that the model is adequate to fit the data. This statistic has an approximate chi-square distribution with (g-2) degree of freedom.

D. The Wald Test

The Wald test is a member of what is known astrinity of classical likelihood testing procedures, the other two being the likelihood ratio (LR) and Lagrange multiplier (LM) tests (Aman et al., 2002). It is an alternative test which is commonly used to test the significance of individual logistic regression coefficients for each independent variable. It is used to test the null hypothesis in logistic regression model that a particular logit coefficient is zero. The Wald statistic is the squared ratio of the unstandardized logistic coefficients to its standardized error.

For each explanatory variable in the model there will be an associated parameter. The Wald test, described by Agresti, 1996; is one of a numbers of ways of testing whether the parameters associated with a group of explanatory variables are zero. If for a particular explanatory variable, or a group of explanatory variables, the Wald test is significant, then would conclude that the parameters associated with these variables are not zero, so that they should be included in the model. If the Wald test is not significant then these variables can be omitted from the model. Wald X^2 statistics can be used to test the significance of individual coefficients in the model and are calculated as follows.

$$Z^2=\left(\frac{\hat{\beta}}{se(\hat{\beta})}\right)^2 \sim X^2(1)$$

Each Wald statistic is compared with a X^2 distribution with 1 degree of freedom. Wald statistics is easy to calculate but their reliability is questionable, particularly for small samples. For the small sample sizes the likelihood ratio test is more reliable than the Wald test (Agresti, 1996)

E. R Squared Statistic

A number of measures have been proposed in logistic regression as analog to R^2 in multiple regressions. The maximum value that the Cox and Snell R^2 attains is less than 1.The Naglekerke R^2 is an adjusted version of the Cox and Snell R^2 and covers the full range from 0 to 1, and therefore it is often preferred, R^2 statistics can be used to indicate how useful the explanatory variables are in predicting the response variable (Bewick et al., 2005)

$$R_{cs}^2 = 1 - \exp\left(-\frac{2}{n}[D - D(\text{model with the variable})\right)$$

The Naglekerke measure is given as follows:

$$R_N^2 = \frac{R_{cs}^2}{R_{max}^2},$$

where $R_{max}^2 = 1 - \exp[2(n)^{-1}D(\text{model with the variable.}]$

3. Outliers and Influential Cases

The observed response for a few of the cases may not seem to correspond to the model fitted to the bulk of the data. Cases that do not follow the same model as the rest of the data are called outliers, and identifying these cases can be useful. Single cases or small groups of cases can strongly influence the fit of logistic regression model. The most useful and important method of perturbing the data is deleting the cases from the data one at a time. Cases whose removal causes major changes in the analysis are called influential (Sanford, 2005).

DFBETA(S) is a diagnostic measure which measures the change in the logit Coefficients for a given variable when a case is dropped. If DFBETAs is less than unity it implies no specific impact of an observation on the coefficient of a particular predictor variable, while DFBETA of a case is greater than 1.0, is considered as potential outlier.

Cook's distance is a measure of the influence of a case. It is a measure of how much the residual of all cases would change if a particular case were excluded from the computation of the regression coefficients. Cook's distance less than unity shows that an observation had no overall impact on the estimated vector of regression coefficients β.

Multicollinearity: refers to a situation where there is either an exact or approximately exact linear relationship among the predictor variables. In other words Multicolinirety is the degree of redundancy or overlap among explanatory variables. The existence of multicollinearity makes it hard to get coefficient estimates with small standard error (Gujarati, 2004).

4. Results and Discussion

Results in this chapter are presented in two separate sections. The first section presents the descriptive results and the second section reveals results of the model employed in this study.

4.1. Coverage of Children's Immunization Status in SNNP Regional State

According to the 2011 Ethiopian DHS, the higher number 81.6 percent children are not fully vaccinated; whereas only 18.3 percent have received all the vaccination services in the region as shown in the Table 4.1 below.

Table 4.1. *Shows the Number and Percentage distribution of Immunization Status of Childrenin SNNPRS.*

		Number	Percent
Immunization status	Not fully vaccinated	801	81.6
	Fully vaccinated	180	18.3

According to the 2011 Ethiopia DHS, the higher (96 percent) children were born at home, whereas only 4 percent are at health centers in the region. As shown Table 4.2 below, immunization status of children is significantly associated with place of delivery (P value<0.05). The highest prevalence

(97%) of children who are bornat home are not fully vaccinated.

Likewise, according to the 2011 Ethiopia DHS, the higher (57.1%) parents are exposed to mass media in the region. As shown in the table below, immunization status of children is significantly associated with exposure to mass media (p-value<0.05). The highest prevalence (71.2 percent) of children whose parents are not exposed to mass media are not fully immunized.

Similarly, childhood immunization status is significantly associated with source of drinking water (p-value<0.05). Accordingly, high prevalence (86.6%) of not fully immunized children are recorded in communities that use unprotected water.

Table 4.2 also shows that the proportion of immunization status of children varies significantly with household's wealth index (P-value<0.05). With regard to this, around half of the population in the region is poor. The highest prevalence (51.6%) children whose parents are poor are not fully immunized.

Similarly immunization status of children is also significantly differs with place of residence (P-value<0.05). According to the 2011 Ethiopia DHS, the higher (83.5 percent) children reside to rural. Regarding to this those children that reside to rural how a higher prevalence (96.3%) of not fully immunized than those that reside to urban.

Likewise, immunization status of children is also significantly associated with age of children (P-value<0.05). The higher proportion (26.3%) of not fully immunized children is observed among those whose age group is in 48-60 months.

As can be seen in Table 4.2, immunization status of children is significantly associated with availability of electric power (P-value<0.05).According to the 2011 Ethiopia DHS, only (18 percent) of the households have electric power in their home. Concerning to this, higher prevalence (93.5%) of not fully immunized children are observed in households with no electric power.

Moreover, immunization status of children varies significantly with mothers' partners educational status (P-value<0.05). The highest proportions (55.2%of not fully immunized children are observed among those whose mother's partners are not educated.

The other variables such as usage of family planning methods, desire for more children, number of under 5 children and sex of child have no significant association with childhood immunization status.

Table 4.2. *Distribution of Socioeconomic, Demographic and Community related Characteristics with Childhood Immunization Status in SNNPR (DHS,2011).*

Variables	Category	Count N(%)	Immunization status		Df	Chi-square (P-value)
			Not fully vaccinated (In%)	Fully vaccinated (In%)		
Place of delivery	Home	942(96)	97.0%	91.6%	1	15.570
	Health center	39(4)	3.0%	8.4%		(0.004*)
Usage of family planning methods	No	741(75.5)	76.8%	69.4%	1	4.595
	Yes	241(24.5)	23.2%	30.6%		(0.101)
Desire for more children	Wants more	574(707)	58.2%	60.0%	1	1.575
	Wants no more	405(29.3)	41.8%	40.0%		(0.455)
Exposure to mass media	Yes	694(57.1)	43.9	71.9	2	17.436
	No	287(28.8)	71.2	28.1		(0.002*)
Number of under 5 children	Less than two	837(85.2)	84.3%	89.4%	1	3.301
	More	145(14.8)	15.7%	10.6%		(0.192)
Sex of child	Male	480(49)	49.6%	45.6%	1	1.992
	Female	502(51)	50.4%	54.4%		(0.369)
Source of drinking water	Protected	314(32.7)	13.4	32.3	1	42.165
	Unprotected	658(67)	86.6	67.7		(0.000*)
Mothers educational status	No education	630(64.1)	68.0%	46.7%		
	primary	340(34.6)	31.1%	50.0%	2	32.306 (0.000*)
	secondary +	13(1.3)	0.9%	3.3%		
Wealth index	Poor	467(48.5)	51.6%	34.4%	1	18.303
	Middle & rich	506(51.5)	48.4%	65.6%		(0.000*)
Availability of electricity	No	994(82)	93.5%	84.4%	1	16.436
	Yes	81(18)	5.9%	14.4%		(0.002*)
Place of residence	Rural	862(80.2)	96.3%	6.7%	1	23.339
	Urban	112(19.8)	3.7%	93.3%		(0.000*)
Toilet facility	Has facility	689(70.2%)	16.2	39.2	1	13.108
	No facility	282(29.8%)	83.8	69.8		(0.041*)

*Significance (p<0.05)

4.2. Results of Logistic Regression Model

A Binary Logistic Regression Analysis is employed to identify the most important determinant factors that determine the acceptance of childhood vaccination services among households of SNNPRS. Before giving interpretation for results of the model first we should check whether or not the model used in this study predicts a response variable well.

The Hosmer-Lemshow Test

If the p-value of the Hosmer-Lemshow Goodness of fit test statistic is greater than α=0.05, we fail to reject the null hypothesis that there is no difference between observed and predicted values, implying that the model fits the data at an acceptable level. The value of Hosmer-Lemshow statistic has chi-square value of 9.205 and a p-value of 0.325 indicating that the model has a good fit as shown in Table 4.3. This shows that there is no significant difference between the observed and predicted model values and hence the model fits the data well.

Table 4.3. *Hosmer and Lemshow Test.*

Chi-square	df	Sig.
9.205	8	.325

Validations of predicted probabilities

The degree to which predicted probabilities agree with actual outcomes is expressed as a classification table. Classification table documents the validity of predicted probabilities. According to Table 4.4, the prediction for children who are not fully vaccinated is more accurate than that for those who are fully vaccinated. This result is supported by the magnitude of sensitivity (14.5 percent) as compared to that of specificity (98.7 percent). Sensitivity measures the proportion of correctly classified events whereas specificity measures the proportion of correctly classified nonevents. The overall correct prediction was 84.1 percent which is an improvement over the chance level.

Table 4.4. *Classification Table of Model with Predictor Variables for Immunization Status of Children in SNNPR (EDHS, 2011).*

Observed		Predicted		
		Completed all vaccinations		Percentage Correct
		No	Yes	
Completed all vaccinations	No	775	10	98.7
	Yes	141	24	14.5
Overall Percentage				84.1

After the assessment/ evaluation of the overall model and goodness of fit test, statistical tests of individual predictors are conducted to identify the determinants for acceptance of the vaccination services among households of SNNPRS.

As shown in Table 4.5 below; mother's educational status, source of drinking water, availability of electric power, place of residence, place of delivery and age of child are found to be the most important determinant factors. Whereas, the other variables such as toilet facility, sex of household head, household wealth index and mothers' partner educational status are not significantly associated with the childhood immunization.

Childhood immunization status is significantly vary with mothers educational status ($p<0.05$). As a result, those children whose mother's educational status is primary are 81.5percent more likely to be not fully vaccinated compared to those whose educational status is secondary & above controlling for the other variables in the model. The result also shows that childhood immunization status is significantly associated with age of the child ($p<0.05$). Accordingly, children in the age group of 6-11 month are0.67timesless likely to be not fully vaccinated compared to those in the age group 48-59month controlling for the other variables in the model.

As shown table below, immunization status of children is also significantly differ with respect to source of drinking water ($p<0.05$). Concerning to this, those that use protected water are0.654 times less likely to be not fully vaccinated compared to children that use unprotected water as a drinking water controlling for the other variables in the model.

Access to electric power is also significantly associated with childhood immunization status as shown table below. Thus those children who have the access are. 549 times less likely to be vaccinated compared to those have no this access keeping the other variables constant.

Place of delivery is also significantly associated with childhood immunization status. Regarding to this those children that born at health centersare0.75times less likely to be not fully vaccinated as compared to children that born at home controlling for other variables in the model.

As shown table below, place of residence is significantly associated with childhood immunization status. Concerning this, children that reside to rural parts of the region are 91.5% more likely to be not fully vaccinated compared to children that reside in urban controlling for other variables in the model.

Table 4.5. *Binary Logistic Regression Model results of Childhood Immunization Status.*

Covariates	β	S.E.	Wald	df	Sig.	Exp(β)	95% C.I for Exp(β)	
							LB	UB
Source of drinking Water	-	-	-	-	-	-	-	-
Protected	-1.061	.211	25.199	1	.000*	0.346	-1.909	.369
Unprotected(ref)	-	-	-	-	-	-	-	-
Mothers' education level	-	-	8.102	2	.017*	-	-	-
No education	.050	.788	1.004	1	.450	1.051	.224	4.927
Primary	.596	.764	6.09	1	.035*	1.815	.406	8.107
Secondary & above(ref)	-	-	-	-	-	-	-	-

Covariates	β	S.E.	Wald	df	Sig.	Exp(β)	95% C.I for Exp(β)	
							LB	UB
Access to mass media	-	-	-	-	-	-	-	-
Yes	-.549	.143	14.745	1	.000*	.577	-.830	-.269
No (ref)								
Placeof delivery	-	-	-	-	-	-	-	-
Health center	-1.388	0.290	5.742	1	.044*	.251	-1.707	.151
Home (ref)	-	-	-	-	-	-	-	-
Place of residence	-	-	-	-	-	-	-	-
Rural	.650	.276	5.522	1	.019*	1.915	1.114	3.292
Urban (ref)	-	-	-	-	-	-	-	-
Age of a child	-	-	11.195	5	.048*	-	-	-
0-5	-19.524	0.007	.000	1	.968	.000	.000	.
6-11	-3.136	1.025	9.356	1	.002*	.043	.006	.324
12-24	.146	.270	.291	1	.590	1.157	.681	1.964
25-34	.245	.262	.877	1	.349	1.278	.765	2.135
35-47	.049	.245	.040	1	.841	1.050	.650	1.696
48-60(ref)	-	-	-	-	-	-	-	-
Constant	.098	1.261	.006	1	.938	1.103	-	-

*Significance ($p<0.05$) ref=Reference category. UB= upper bound LB= lower bound

Outliers, Influential Diagnostics and Multicollinearity

DFBETAs are all less than unity implying no specific impact of an observation on the coefficient of a particular predictor variable. The result also shows that cook's distance values are all less than unity showing that an observation had no overall impact on the estimated vector of regression coefficients β. The result of the maximum value of analog of Cook's influence statistics for each predictor variable is also less than 1.0. Therefore, there is no potential influential observation

Multicollinearity in logistic regression is detected by examining the standard errors for the β coefficients. A standard error larger than 2.0 indicates numerical problems, such as multicollinearity among the independent variables, zero cells for a dummy-coded independent variable because all of the subjects have the same value for the variable, and 'complete separation' whereby the two groups in the dependent event variable can be perfectly separated by scores on one of the independent variables. However, none of the coefficients of the independent variables in this analysis had a standard error larger than 2.0.

5. Conclusions and Recommendations

5.1. Conclusions

This study revealed the socio-economic, demographic and community characteristics that affect completeness of the immunization services among children in SNNPRS. A Binary Logistic Regression Model is employed to identify the determinant factors. Results of the model show that: mothers' educational status, age of child, source of drinking water, place of delivery, place of residence and availability of electric power are the most important determinant predictors of childhood immunization status.

As findings of this study show, children whose families have the access to mass media are at a higher risk of lower immunization status. This may be because of the fact that mass media is related to urbanization, several services, opportunities and higher living standards. Moreover, since most of the rural areas in the region have no this access, where majority of the children resides, the government and other concerned bodies should address this problem to attain the wellbeing of rural children by strengthening health education programs and by addressing the immunization services to the poor and vulnerable communities in rural parts of the region. This finding is consistent with (Smith and Haddad, 2006; Escobal et al. 2009).

As this study shows, there is also a significant association between maternal education and full immunization. Education helps to improve health seeking behavior of an individual. This finding is consistent with other literatures like Tadesse et al., 2010 and Breiman et al., 2009, that found that maternal education was a significant predictor of completeness of immunization because highly educated mothers will be more aware of the importance of immunization. The role of maternal education as an important cause of immunization uptake has also been shown by Mahy, 2009 and Onyiriuka, 2010.

Source of drinking water is also an important community factor that affects the immunization status of children in SNNPRS. The findings of this study show that children in communities that use unprotected water are more likely vulnerable to be less vaccinated. The access to unsafe water is regarded as the main cause of infectious diseases such as diahrea and intestinal parasites (Smith et al, 2009).Moreover, improving access and quality to safe water not only reduces transmission of waterborne diseases but also saves women the extra time they spend on carrying water which can be allotted to child care and income generating activities.

Age of child is also one of the most important determinant factors to the completeness of immunization among children in the region. Children at the early months are more likely to be fully immunized than any older age groups. This could be because of mother's ability to care for the child and also due to the reduced care that parents give to older children especially if there are younger children in the family (UN, 2012).

The relationship between rural/urban differential with full Child Immunization is also significant. Urban and rural areas are broadly different in the receipt of vaccines. Urban areas had the highest coverage rates for most vaccinations when taken separately, and the highest percentage of children who had received the full vaccines. This is probably partially due to the general distribution of healthcare facilities in the region. It could also be attributed to the lack of awareness of the importance of vaccination between mothers in rural areas in comparison to those in urban areas (Adebiyi, 2013).

Place of delivery is also significant in this study, the same was found in the study conducted in Niger Delta area of Nigeria by Oyoita et al., 2012. A child that is born in a health facility would have more access to immunization than a child born at a non health facility. At birth, a child is given a Polio vaccine and this makes the parent to be aware of immunization. Similar findings have been reported in previous studies (Luman et al., 2009 and Oladokun et al., 2010).

5.2. Recommendations

The result suggested that children of uneducated mothers are more vulnerable to be not fully immunized. Therefore, it is useful to improve mothers' access to education in all areas in order to address the problem through improving their income earning capacity and also enhancing the quality of care and attention they can provide to their children.

Similarly, children in communities with no electric power were also more vulnerable to the incompleteness of immunization services. So it is recommended that the government or any other responsible bodies should address the problem of electric power to the unprivileged communities.

This study also shows that children whose mothers attended antenatal clinics are more likely to be fully immunized. The Government should strengthen antenatal clinic by training more health care workers. SNNPRS health bureau should conduct immunization campaign frequently focusing on all the required vaccines.

In general, results of this study manifest that the differences in the immunization status of children is associated with uneven distribution of the population and limited healthcare facilities, cultural practices, inequality in the distribution of services and resources. Based on results of this study, I recommend that education programmes that can target poor and uneducated people should be put in place so that they are able to make informed decisions regarding immunization of their children. Free health facilities should be made available to every mother so that poor mothers can easily access them.

Finally the SNNPRS Government should improve Supplemental immunization activities by preparing programmes that should be regularly carried out until routine immunization coverage is improved in the region.

List of Abbreviation

CSA	Central Statistical Association
EDHS	Ethiopian Demographic and Health Survey
EPI	Expanded program on Immunization
NCHS	National Center for Health Statistics
MDG	Millennium Development Goal
MOH	Ministry of Health
UN	United Nations
UNICEF	United Nations Children's Fund
US	United States
SNNPRS	Southern Nations, Nationalities and Peoples Regional State
WHO	World Health Organization
WMS	Welfare Monitoring Survey

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